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The diffusion of renewable electricity in the presence of climate policy and technology learning: The case of Sweden

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ABSTRACT

The overall objective of this paper is to analyze the impact of climate policy and technology learning on future investments in the Swedish power sector. Methodologically we assess the lifetime engineering costs of different power generation technologies in Sweden, and analyze the impact of carbon pricing on the competitive cost position of these technologies under varying rate-of-return requirements. We also argue that technological learning in the Swedish power sector – not the least in the case of wind power – is strongly related to the presence of international learning and R&D spillovers, and for this reason capacity expansions abroad have important influences of the future cost of power generation in Sweden. The results suggest that renewable power will benefit from existing EU climate policy measures, but overall additional policy instruments (e.g., green certificate schemes) are also needed to stimulate the diffusion of renewable power. Moreover, under a recent European Commission scenario and using estimated learning rates for wind power and the combined cycle gas turbine (CCGT), wind power gains considerable competitive ground due to international technology learning impacts. These latter results are, however, very sensitive to the assumed learning-by-doing rates for wind power and CCGT, respectively.

Contents

1. Introduction

New investments in the European electric power sectors are affected by a number of energy and climate policy measures at the European Union level. The major goals of the most recent policy proposals are to reduce greenhouse gas emissions by 20%, increase energy efficiency by 20% and increase the amount of renewable energy to 20%, each of these three until the year 2020. These targets complement previous commitments made at the Kyoto and Rio meetings. In order to comply with the Kyoto Protocol as well as strive towards these long-term targets for carbon dioxide reduction, the EU has introduced a system of emissions trading (EU ETS) for CO_2 for selected sectors of the European economies. As a consequence of the introduction of the EU ETS in 2005 a number of industry sectors can now trade emission allowances. The energy industries that are affected at this stage are heat and power plants with a capacity of more than 20 MW.

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In 2006 the nuclear- and hydro-dominated power sector in Sweden accounted for only about 2% of total CO_2 emissions in the country. It could therefore be comfortable to say that a carbon policy does not affect the power sector in Sweden. This is, however, not true since future power demand in Sweden is likely not to be met by new investments in nuclear and hydropower,[1] but instead by either fossil-fueled power based on coal or gas or on renewable energy sources such as wind, biomass, solar etc. The expected annual increase in electric power demand in Sweden is approximately 0.6–1.6%. This implies that new investments in power capacity will be necessary in the coming 10–20 years [1,2], and a carbon policy – such as emissions trading through EU ETS – is likely to affect future power generation technology choices. However, it remains unclear to what extent existing climate policies will affect the competition between fossil-fueled and renewable energy sources in the generation of power.

The overall objective of this paper is to analyze how future investments in the Swedish power sector can be affected by carbon pricing policies. Carbon-free power technologies, such as wind power, will have to compete with more mature technologies (e.g., fossil-fueled technologies such as gas and coal power). In recent years plants with the combined cycle gas turbine (CCGT) technology has increased their competitiveness and often they represent attractive alternatives for new investment in power generation (e.g., [3]). Still, what happens when a carbon pricing policy is implemented? What level of the price of carbon will be required to equalize the generation costs of different renewable energy technologies with that of CCGT? The answers to these questions will depend on a number of uncertain factors, and the present paper highlights a number of factors that condition future power generation technology choices in Sweden in the presence of carbon pricing. In the first part we focus on the price of carbon following current and future climate policies and to what extent this will affect the relative competitiveness of the available investment alternatives. The second part pays special attention to the possible impacts of technology learning – and the resulting cost decreases – on the economics of power generation in the presence of climate policy. While the first part considers the majority of power generation technologies available in Sweden, the second part focuses solely on the competition between CCGT and the cheapest renewable power alternative, onshore wind power.

Methodologically, we approach the above issues from the perspective of a power generator who considers investing in new generation capacity. This implies that we first of all assess the lifetime engineering costs of different power generation technologies in Sweden, and analyze the impact of carbon pricing on the competitive cost position of these technologies under varying rate-of-return requirements. This is achieved by employing the levelized cost methodology, a variant of the discounted cash-flow methodology (DCF) often used by electricity companies for investment decisions (see Section 2). The cost calculations are performed both with and without existing policy instruments (e.g., investment subsidies, environmental taxes, fees, etc.). In addition, in the case of wind and gas-fired power we also include technological learning in the analysis and the effect of international learning-by-doing on the life-time costs. This power generator eye-view of the investment decision permits us to make a number of remarks about, for instance, how the diffusion of renewable energy in the Swedish power sector will be influenced by carbon emission pricing and how sensitive these conclusions are to changes in the price of carbon as well as to different future cost developments for the most important power technologies.

The paper differs from past research efforts and contributions to the energy economics literature in a number of ways. The focus on the Swedish case will allow us to draw specific conclusions about how an international carbon policy may affect the power sector in a small open economy, providing thus a context-rich analysis of policy impacts and implications. Earlier studies have often focused on power generation in general and on other geographical areas (e.g., [4,5]). Söderholm and Strömberg [6] analyze how the power sector in Europe will comply with a mandatory emission reduction program, and conclude that many generators will consider investments in existing technologies (i.e., fuel conversions, lifetime extensions, efficiency improvements, etc.) in the case of a carbon pricing policy. Following another research tradition, Unger [7], Unger and Ahlgren [8] and Rydén [9] employ the bottom-up energy systems model MARKAL and analyze the future development of the Nordic energy system in the presence of different climate and renewable energy policies. While this type of model work is very useful for studying technology choice under different policy scenarios – not the least given its detailed representation of available energy technologies and their costs – it is limited in its characterization of institutional obstacles to new investment and perfect foresight in the investment decision process is typically assumed. This suggests that the adopted power generator eye-view of the investment decision process – with its focus on policy and technology cost uncertainties – should be able to complement much of this previous work.

The paper proceeds as follows. Section 2 presents our methodological approach for performing the cost simulations, as well as how technology learning affects the economics of power generation. We also discuss the cost data used in the simulations. Section 3 provides simulation results of the power generation costs in the presence of a carbon price; account is taken of different carbon price scenarios as well as of varying technology learning effects. Finally, Section 4 provides some concluding remarks and implications.

2. Methodological approach and data

2.1. The assessment of generation costs for new power generation

As a first step towards analyzing the impact of carbon prices on the Swedish power sector, we assess the project costs for the different investment alternatives and use these to simulate what level of carbon pricing that will equalize the generation cost for each alternative with our benchmark alternative, CCGT. Second, our cost simulations are rather meaningless unless put into a relevant policy context. We therefore make use of previous model estimates of the marginal abatement cost of attaining future emission targets (caps) in EU ETS. Given the levelized power generation cost estimates and the resulting break-even carbon prices we can analyze the impacts on investment behavior of anticipated climate policy measures.

In order to compare the economics of different power generating technologies we use an extension of traditional DCF and calculate the levelized costs LC_i for each technology i.[2] This approach generates the net present value (NPV) of all power generation costs divided by the present value of the power plant's lifetime output. We get:

$$\mathrm{LC}_i = \frac{\sum_{t=0}^{T}(I_{it} + M_{it} + F_{it} + C_{it})\rho}{\sum_{t=0}^{T} O_{it}\rho} \tag{1}$$

where I_{it} represents total investment costs in time period t (t = 1, . . ., T), M_{it} operation and maintenance costs, F_{it} fuel costs, C_{it} the

[1] The Swedish Government has decided that nuclear power should be decommissioned (although substantial investments in existing nuclear power stations do take place), and new investments in hydropower are in large restricted by law.

[2] See also, for instance, Corey [41], Bemis and DeAngleis [33] and Söderholm and Strömberg [6].

total costs of purchased CO_2 emission allowances, and O_{it} is the net electrical output. The discount factor ρ equals $(1 + r/100)^{-t}$ and r represents the private discount rate. The total costs of CO_2 emission allowances are in turn determined by the product:

$$C_{it} = P_t^C(O_{it}\alpha_i) \tag{2}$$

where P_t^C represents the emission allowance price measured in US$ per ton CO_2, and α_i is the emission factor expressed in ton CO_2 per kWh electricity generated.[3] The LC model generates thus an internal average lifetime cost per unit electricity generated, expressed in US$/kWh.

Given that we are interested in analyzing what carbon price will equalize the generation costs for our benchmark alternative (CCGT) and its competitors (e.g., wind power), we set $LC_{wind} = LC_{CCGT}$ and solve for the break-even carbon price, P_t^{C*}, given a certain rate-of-return requirement, r. We have:

$$\frac{\sum_{t=0}^{T}(I_{\text{wind},t} + M_{\text{wind},t})\rho}{\sum_{t=0}^{T}(O_{\text{wind},t})\rho} = \frac{\sum_{t=0}^{T}(I_{\text{CCGT},t} + M_{\text{CCGT},t} + F_{\text{CCGT},t} + P_t^{C*}(O_{\text{CCGT},t}\alpha_{\text{CCGT}}))\rho}{\sum_{t=0}^{T}(O_{\text{CCGT},t})\rho} \tag{3}$$

In a similar manner, the left hand side of Eq. (3) can be replaced by the corresponding variables for the remaining technologies in our comparison. We can thus simulate the level of the carbon price that is required to put the different power sources on equal footing compared to the CCGT alternative.

We conduct the analysis for different discount rates, and use a private discount rate ranging from 4% to 15% and an average lifetime of 20 years. With an interval discount rate we cover a wide range of rate-of-return requirements, partly because electricity companies are unwilling to reveal their discount rates but not the least since this exercise permits us to analyze how future uncertainties in general (e.g., about costs and policy) affect the relative economics of different technologies. Finally, the 'break-even' carbon prices can then be compared to estimates of the carbon prices required to ensure compliance with given climate policy targets.

Before proceeding, it is worth mentioning that the DCF methodology can be questioned for its simplicity and one important shortcoming of the model is that it does not explicitly address the presence of flexibility and irreversible investments [10]. In a typical investment situation the firm has the option, or the opportunity, not to invest. This option can include the ability to delay investments, expand or contract a project, and to shut down operations. In our case this could imply the opportunity for a power company to apply a different fuel mix or postpone an investment decision. Investing exercises this option and hence creates an opportunity cost that ideally should be included in the decision-making process. Real-option value techniques take this opportunity cost into consideration and assign a value to the option. The result from a DCF technique could therefore overstate the value of irreversible investments. Real-option techniques are, however, complex to employ due to the variety of options present in real-life situations, and are thus more suitable for direct investment decision-support rather than for the type of generic economic assessments presented in this paper.

2.2. Modeling the impact of technology learning

An important determinant of future power generation costs is technology learning. The concept of learning-by-doing is well established in the economics literature starting with the seminal study by Arrow [11]. It has been suggested that cost reductions for a certain technology will be closely related to the installed cumulative capacity (i.e., a proxy for learning) of that same technology (e.g., [12]). The corresponding learning curve concept has been studied for a number of energy technologies; see Klaassen et al. [13] and Söderholm and Klaassen [14] for recent examples of technology learning studies in the wind power sector and Claeson Colpier and Cornland [15] for an empirical analysis of learning in CCGT.

One way of incorporating the effect of technology learning on cost trajectories for the chosen technologies is thus to assume that the investment costs are a function of the installed cumulative capacity so that, for instance:

$$I_t = A(\mathrm{CI}_t^{\beta_L}) \tag{4}$$

where A is the cost measured in US$ per MW at unit cumulative capacity, CI_t the cumulative capacity and β_L the so-called learning elasticity. This is the most common formulation of the learning curve concept and thus rests on the assumption that investment costs are only reduced with the diffusion of new capacity. By taking the natural logarithm of the expression in Eq. (4) and running a linear regression we obtain an estimate of β_L, which represents the percentage cost reduction if cumulative capacity increases by one percent. This is commonly referred to as the learning elasticity (or learning index). The learning elasticity can be used to derive the learning-by-doing rate, which equals $1 - 2^{\beta_L}$. For instance, if $\beta_L = -0.15$ this yields a learning-by-doing rate of 0.1, implying that a doubling of the cumulative capacity will reduce costs by 10%. A review of estimated learning rates for a number of energy technologies can be found in IEA [16] and McDonald and Schrattenholzer [17].

The traditional learning curve concept has been extended to also take into account the impact of cumulative R&D expenses, often referred to as learning-by-searching (e.g., [14,18]). These expenses accumulate over time to generate a R&D-based knowledge stock, K_t, so that:

$$K_t = (1 - \gamma)K_{(t-1)} + \mathrm{RD}_{(t-x)} \tag{5}$$

where RD_t are the annual R&D expenditures, x the number of years before R&D expenditures add to the knowledge stock and γ the annual depreciation rate of the knowledge stock. This means that we can restate our investment cost equation so that:

$$I_t = A(CI_t^{\beta_L})(K_t^{\beta_K}) \tag{6}$$

where β_K is the learning-by-searching elasticity and the corresponding learning-by-searching rate is calculated accordingly $(1 - 2^{\beta_K})$ indicating how a doubling of accumulated knowledge would propel a decrease in technology costs.

In the empirical part of this paper we investigate the impact of technology learning on the competitive positions of CCGT and wind power, respectively, by partly drawing on previous estimates of the learning rates for these technologies and partly on own preliminary estimates of the learning rate for Swedish wind power (see Appendix). Some of the previous studies do control for the impact of domestic R&D expenses, while rather many, however, use the simple learning curve relationship outlined in Eq. (4). Overall, it is however important to acknowledge the specific context in which technology learning affects power generation costs in Sweden.

In the Swedish case it is reasonable to assume that the lion share of technological learning for domestic power sources such as wind energy and CCGT take place abroad; this implies that any cost reductions will be largely independent of domestic investments in these technologies. Cost reductions are instead determined by world growth in, for instance, CCGT and wind power capacities,

[3] We assume emission factors of 0.65 and 0.22 kg CO_2 per kWh for coal and gas, respectively ([38]).

Table 1
Power generation project data and costs.

Plant type	Capacity (MW)	Levelized cost (US$/kWh)			
		Without existing policy instruments		With existing policy instruments	
		$r = 5\%$	$r = 10\%$	$r = 5\%$	$r = 10\%$
Combined cycle gas turbine (CCGT)	400	5.8	6.3	6.0	6.5
Biomass combined heat and power (CHP)	80	9	11.6	5.1	7.9
Coal steam cycle	400	8.1	7.1	3.9	6.3
Coal carbon capture and storage (CCS)	400	9.8	11.1	7.4	11.3
Waste CHP	30	2.6	7.1	8.6	12.9
Wind onshore	4.25	7.6	10.4	8.6	7.6
Wind onshore	40	6.4	8.8	10.7	12.0
Wind offshore	150	9.9	13.8	6.4	9.0
Wind offshore	750	11.1	15.4	5.5	10.0
Nuclear	1600	3.5	4.7	4.3	5.5

Source: Authors' estimates are based on Hansson et al. [3].

and thus also by the implementation of climate and energy policies outside Sweden. Moreover, since the large majority of the wind turbines installed in Sweden are manufactured in Denmark it is also plausible to assume that future cost reductions in Swedish wind power are determined by cumulative Danish R&D efforts that 'spill over' to Sweden as Danish wind turbines are imported (e.g., [43]).[4] This type of international influence is largely ignored in previous empirical research on energy technology learning rates. Still, in the Appendix to this paper we present some very preliminary econometric results, which show that both international learning and the Danish R&D-based knowledge stock[5] do play important roles in influencing the cost of installed wind power mills in Sweden. However, domestic public R&D support does not appear to have a statistically significant impact on investment costs. Overall this implies that the future development of Swedish wind power costs can essentially be treated as an exogenous variable in the cost simulations.

In Section 3.2 of this paper we make use of existing projections of international capacity expansions in gas-fired power and wind energy as well as estimates of the respective learning-by-doing rates to assess the future costs of these power sources. Due to data availability the impact of R&D spillovers from Denmark and/or other future wind turbine suppliers to Sweden are, however, ignored in the estimations. Put differently, the latter implies that we assume that the annual public R&D expenses in Denmark will be just about high enough to maintain a constant knowledge stock over time given a certain rate of annual knowledge depreciation (γ).

2.3. Data inputs: power generation costs and carbon allowance prices

The data for the cost simulations originate from Hansson et al. [3], and involve the average lifetime costs for representative power plants, although in practice investment costs and operation and maintenance cost can be highly site-specific. Table 1 presents project data and engineering cost estimates for a number of Swedish power generation alternatives assuming 5% and 10% private discount rates. We present both the private generation costs (i.e., excluding any policy instruments) and the costs in the presence of existing policies. These policies include the Swedish green certificate scheme, a sulfur tax and a nitrogen oxide fee for fossil-based power, a CO_2 tax for heat generation in combined heat and power generation plants, a tax on the thermal heat from nuclear power generation, and an 'environmental bonus' for wind power.[6] However, we do not here include the price on carbon emissions in the EU ETS as these impacts are analyzed below in this paper.

Although hydropower accounts for about half of power generation output in Sweden, it is not included in the comparison as new investments in large-scale hydro are prohibited by law in Sweden and since the cost of hydropower differs substantially across different sites, making it difficult to present generic cost estimates. Overall the cost figures show that in the absence of taxes and subsidies, nuclear and gas-fired power are the cheapest alternatives given a discount rate of 10%. The cheapest renewable alternatives, except waste power, are the two onshore wind power projects. At low discount rates the economics of waste incineration appears favorable, but since the technology is so capital-intense its competitive position is highly sensitive to the use of higher rate-of-return requirements.

When it comes to the fossil-fuel-based technologies, on a private cost basis gas-fired power is likely to be favored over coal. The combined cycle gas turbine possesses – in contrast to nuclear energy and coal-fired power – many of the characteristics suitable in times of deregulation and slow demand growth. Most importantly, low capital costs, short lead times, and the possibility of adding small capacity increments, enable power producers to follow demand developments more closely, and reduce uncertainties and costs (e.g., [19]). In addition, coal carbon capture and storage (CCS) is still a fairly 'new' technology and its costs are currently considerably higher compared to the alternative technologies.[7] The recent construction of a gas-fired power station in the south of Sweden using Norwegian gas illustrates the favorable economics of the gas alternative – at least when the infrastructure for transporting the gas is at place [20]. The above largely motivates the use of gas-fired power as a benchmark towards which the economics of renewable energy sources and coal CCS can be assessed.

In the recent past no carbon tax was paid for fuels used in the Swedish power sector. However, with the introduction of the EU-wide emissions trading scheme in 2005 carbon emissions have begun to carry a price also in this sector [21]. The trading system

[4] In the microeconomic literature on technological spillovers it is common to identify a metric, in many cases 'technological closeness' (e.g., [42]), as a way of measuring the intensity of these spillovers. Given that most wind turbines are imported into Sweden it makes sense to use import shares as measures of intensity [43]. Thus, the foreign R&D-based knowledge stock would equal the import-share-weighted average of the domestic R&D stocks of the relevant trade partners. In our empirical estimation (see Appendix), we implicitly assume a 100% import share for Danish wind turbines into Sweden.

[5] This knowledge stock has been computed as in Eq. (4). See Appendix for details.

[6] The 'environmental bonus' is essentially a production subsidy for wind power generation. It is currently being phased out, but may be replaced by other policy instruments in the case of offshore wind power.

[7] Although the technology of pumping CO_2 into oil-fields, i.e., enhanced oil recovery, has been known and used for some time, the CCS technology is fairly new and still not yet used on a commercially basis in the European power sector.

increases the technology costs for carbon intense technologies and possibly rules out a number of them for future investments. If the price on carbon is low new investments in gas-fired technology could be preferable to investments in, say, wind and/or biomass-generated power. The competitiveness of the different power technologies will also be determined by future cost developments (i.e., technology learning effects). In the Swedish case it is reasonable to assume that both the allowance price of carbon as well as technology learning will (primarily) be external to investment decisions taken in the Swedish power sector, i.e., these impacts can essentially be treated as exogenous variables in the empirical analysis.

Finally, our cost estimates must be related to specific carbon prices following climate policy agreements. The carbon prices used in the following analysis build on model estimations in which the economic consequences of pre-determined abatement or concentration targets are analyzed. These models assume that an exogenous reduction goal is set (e.g., the Kyoto commitment or a certain maximum CO_2 ppm level) and then calculates the price of carbon that is required to meet this obligation. The estimates that we use stems from Edenhofer et al. [22] in which the results from 10 climate-economy models are reported. The numbers are reported for several atmospheric concentration targets, but we focus on the 450 and 550 ppm CO_2 scenarios, and the corresponding marginal abatement cost between 2020 and 2030. Although these studies calculate the abatement cost and/or carbon tax that is needed to meet the target in 2100, we limit our analysis to the costs facing an investor in the coming decades. Following the mean value from these studies we base our empirical analysis on a price of carbon emissions of 20 and 40 US$/t$CO_2$, respectively. These numbers also fall well in line with similar projections of the mid-term EU ETS permit price.

3. Empirical results

3.1. Estimates of break-even carbon prices

Table 2 presents the cost-equalizing carbon prices (with and without any policy instruments) of different technologies compared to the benchmark technology CCGT. Carbon prices for a wide range of rate-of-return requirements are presented, and the estimates in parentheses include the impact of policy instruments

The results show, for instance, that in order to make onshore wind power (40 MW) and CCGT equally expensive on a private cost basis the carbon price has to be between 7 and 115 US$/t$CO_2$ depending on the discount rate used. However, if existing policy instruments are accounted for only low carbon prices are needed in the case of high discount rates. The offshore wind alternatives are considerably more expensive and require carbon prices in the range of 88–334 US$/t$CO_2$ on a private cost basis, and even in the presence of existing policies relatively high carbon prices are needed to make offshore wind profitable.

Fig. 1 displays the results from Table 2 in four different diagrams. From these we see that when the discount rate increases the policy support needed for biomass and wind power increases due to the high capital intensity associated with these types of plants. In general, the steeper the slope the relatively more capital intense the relevant power technology is, and the CCGT option gains in competitiveness as higher discount rates are used. It is also clear that both wind power and biomass are relatively dependent on existing policy instruments (e.g., green certificates) in order for them to be equally expensive with CCGT power. If carbon pricing in EU ETS would be the only policy instrument in force, high prices (often above 100 US$/t$CO_2$) would be needed to stimulate the diffusion of renewable energy sources at the expense of CCGT.

We now turn to the question of which carbon prices are the most compatible with predictions of the carbon prices following from future climate policies. Tables 3 and 4 summarize investment alternatives that will be the cheapest under two different carbon prices, 20 and 40 US$/t$CO_2$, respectively. As was noted above, these estimates correspond to typical projections of EU ETS prices over the coming decade.

Table 3
The economics of power generation technologies under Kyoto scenarios (no policy instruments, no technological learning).

	20 US$		40 US$	
	$r = 5$	$r = 10$	$r = 5$	$r = 10$
Wind 4.25	Gas cheaper	Gas cheaper	Gas cheaper	Gas cheaper
Wind 40	Wind cheaper	Gas cheaper	Wind cheaper	Gas cheaper
Wind 150	Gas cheaper	Gas cheaper	Gas cheaper	Gas cheaper
Wind 750	Gas cheaper	Gas cheaper	Gas cheaper	Gas cheaper
Coal 400 CCS	Gas cheaper	Gas cheaper	Gas cheaper	Gas cheaper
Bio 80	Gas cheaper	Gas cheaper	Gas cheaper	Gas cheaper

Table 4
The economics of power generation technologies under Kyoto scenarios (policy instruments, no technological learning).

	20 US$		40 US$	
	$r = 5$	$r = 10$	$r = 5$	$r = 10$
Wind 4.25	Wind cheaper	Wind cheaper	Wind cheaper	Wind cheaper
Wind 40	Wind cheaper	Wind cheaper	Wind cheaper	Wind cheaper
Wind 150	Wind cheaper	Gas cheaper	Wind cheaper	Gas cheaper
Wind 750	Gas cheaper	Gas cheaper	Gas cheaper	Gas cheaper
Coal 400 CCS	Gas cheaper	Gas cheaper	Gas cheaper	Gas cheaper
Bio 80	Bio cheaper	Bio cheaper	Bio cheaper	Bio cheaper

Table 2
Carbon prices (US$/t$CO_2$) required to equalize the levelized unit cost of different alternative power sources with the cost of CCGT (simulation results including the impact of policy instruments in parenthesis).

Discount rate	Wind 4.25 onshore		Wind 40 onshore		Wind 150 offshore		Wind 750 offshore		Coal 400 CCS		Biomass 80	
4	35	(−58)	7	(−86)	88	(−6)	117	(24)	98	(98)	73	(−23)
5	45	(−48)	15	(−77)	103	(10)	134	(41)	101	(102)	82	(−14)
6	56	(−37)	24	(−69)	119	(26)	151	(58)	105	(105)	91	(−5)
7	67	(−26)	33	(−60)	136	(42)	170	(77)	109	(109)	101	(5)
8	78	(−15)	42	(−50)	153	(60)	188	(95)	113	(113)	111	(15)
9	90	(−3)	52	(−41)	170	(77)	208	(115)	117	(117)	122	(26)
10	102	(9)	62	(−31)	189	(95)	228	(135)	121	(121)	132	(36)
11	114	(21)	72	(−21)	207	(114)	248	(155)	124	(125)	143	(47)
12	126	(34)	82	(−10)	226	(133)	269	(176)	128	(129)	154	(58)
13	139	(46)	93	(0)	246	(153)	290	(197)	132	(133)	166	(70)
14	152	(60)	104	(11)	266	(172)	312	(219)	136	(136)	178	(81)
15	166	(73)	115	(22)	286	(193)	334	(241)	140	(140)	189	(93)

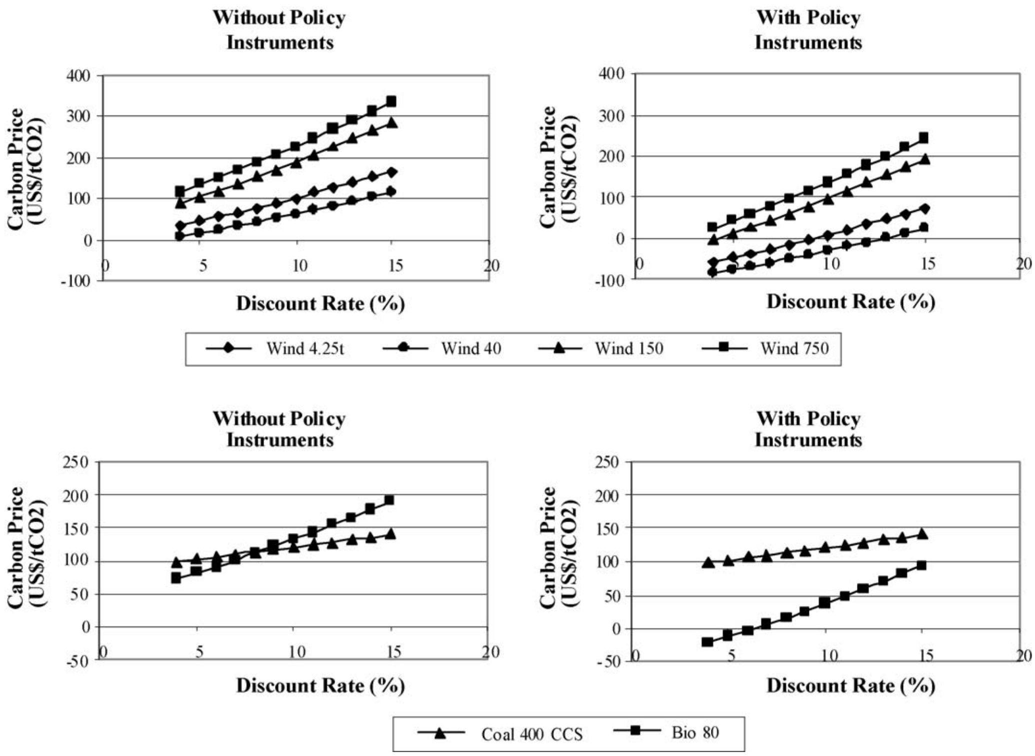

Fig. 1. Carbon prices required to equalize the cost of different power sources with the cost of CCGT (US$/t$CO_2$).

With a price of 20 US$ and a 5% discount rate, the results show that all technologies are more expensive on a private cost basis than CCGT except the largest onshore wind power project. With a higher rate-of-return requirement that project also fails to be competitive against gas power. Even at a higher carbon price (40 US$), CCGT turns out to be favored over the alternatives. If on the other hand we include existing policy instruments we see that the renewable alternatives increase their competitiveness substantially, and this confirms the above conclusion that the green certificate scheme in Sweden is critical for stimulating increased use of renewable electricity in the country.

Wind will thus benefit from planned climate policies but perhaps not as much as one could expect. Costs vary considerably between different sites and projects, both onshore and offshore, and the development can be constrained in the future by difficulties in finding appropriate sites. Both wind and biomass are heavily dependent on the existing policy instruments if these should be favored over CCGT. Biomass also gains from carbon policy but considering the intense competition for biomass, additional utilization in the energy sector can be difficult to achieve. This implies that gas may grow in importance in the future even in the presence of climate policy (unless there is a revival for nuclear power generation). Recent model estimations show that any future growth of wind power in Scandinavia affects both nuclear and gas technologies; Holttinen and Tuhkanen [23] suggest that if the use of wind power increases to about 8–12% of total power generation, it will primarily replace nuclear power. An important result of the analysis is also that the CCGT option gains substantial competitive ground from the use of higher rate-of-return requirements. This suggests that one of the most effective means of promoting renewable energy sources such as wind power is to reduce the uncertainties about future policies.

3.2. Empirical results in the presence of technology learning

The cost simulations in the previous section did not address the potential effect of technological learning on power generation costs. Learning or experience curve methodology can be used when analyzing the future cost developments for new and existing power generation technologies (e.g., [24,25]). Hence, an analysis of future cost reductions must be based on a projection or scenario on how the future could unfold. Numerous projections of future energy supply patterns exist, all based on various assumptions regarding e.g., population and economic growth levels. In this paper we follow the baseline scenario in EU Energy and Transport – Trends to 2030 [26], and make use of the projected installed capacities of wind power and CCGT and the projected gas prices until 2030. This means that we can use learning rates in combination with projections of installed capacity and calculate the corresponding cost reductions due to technology learning. The baseline scenario projects that the installed capacity of wind power and gas power will increase by 258% and 73%, respectively, between 2005 and 2030, and that the gas price will increase by 38% during the same period.

In order to assess future cost reductions for wind and CCGT technologies, we rely on the average estimated learning rates for investment costs in these technologies as reported in Pettersson [27]; these are 0.11 for wind power and 0.10 for gas power.[8] A learning rate for wind power of 0.11 could be considered relatively low compared to the global learning curve estimates derived in, for instance, Junginger et al. [28] where the authors argue that a learning rate ranging between 0.15 and 0.23 is a likely rate for wind. In order to complement previous estimates of learning rates for wind power, we estimate a learning curve for Sweden (see Appendix for details). The learning-by-doing rate for wind power in Sweden is here estimated at 0.23 and thus corresponds well to previous studies, which assume essentially global (rather than national) learning. The combination of the learning rates and the projections of installed capacity of wind power and CCGT internationally and the corresponding cost decreases has there-

[8] These numbers are based on the average learning rates estimated in a wide range of previous studies. See Pettersson [27] for details.

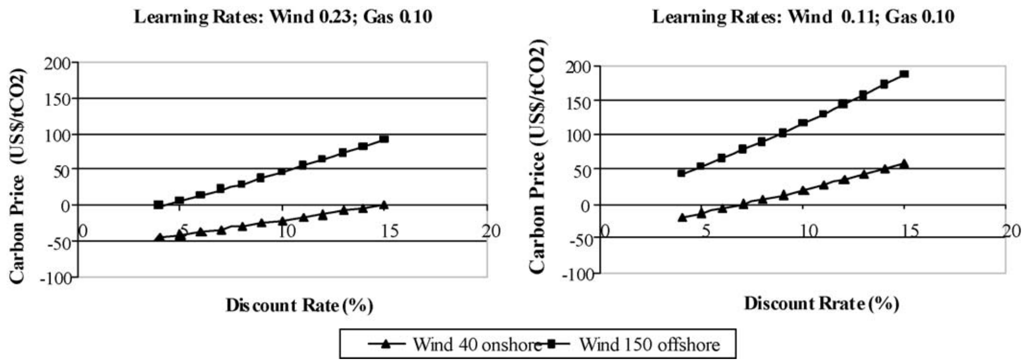

Fig. 2. Carbon prices required to equalize the cost of wind power with the cost of CCGT (technology learning included, constant gas prices) (US$/$tCO_2$).

Table 5
The economics of CCGT and wind power generation in the presence of climate policy, technology learning and constant gas prices.

	20 US$ $r = 5\%$	40 US$	20 US$ $r = 10\%$	40 US$
	Learning rates: wind 0.23; gas 0.10			
Wind 40	Wind cheaper	Wind cheaper	Wind cheaper	Wind cheaper
Wind 150	Wind cheaper	Wind cheaper	Gas cheaper	Gas cheaper
	Learning rates: wind 0.11; gas 0.10			
Wind 40	Wind cheaper	Wind cheaper	Equally expensive	Gas cheaper
Wind 150	Gas cheaper	Gas cheaper	Gas cheaper	Gas cheaper

after been implemented in the levelized cost routine described in Section 2.

We use both the average and the Swedish learning rates for wind power as well as the average rate for CCGT in the model simulations and calculate the new carbon price levels that are needed in order to make wind power as attractive as CCGT given the EU energy scenario described above. Our focus is on CCGT and two wind power options, onshore wind 40 MW and offshore wind 150 MW. The new results thus build on the assumption that the investment costs change over time, i.e., the learning effect takes place in building the plants and not in operating them. In addition, we also present the results for the carbon price levels with constant and increasing gas prices, respectively. Overall we only use the private generation costs in the simulations.

Fig. 2 displays the carbon prices that are required to equalize the costs of wind power with those of CCGT when learning is taken into consideration but with constant future gas prices. The results suggest that under current scenarios wind becomes considerably cheaper in the future – for both the high and low learning rates – and overall lower carbon prices are needed to make wind power as attractive as CCGT (compared to the zero-learning case). The results, though, also show that the outcome is very sensitive to the choice of learning rate for wind power. For instance, at a 10% discount rate the carbon price needed to make the offshore wind alternative equally expensive as CCGT equals about 50 US$/$tCO_2$ in the case of a 23% learning rate, but the corresponding price increases to well above 100 US$/$tCO_2$ if the learning rate is 11%. This suggests that reliable estimates of these learning rates become important, but so far the empirical literature has failed in generating robust estimates [29,30].

Table 5 shows the technology choice outcomes when either a 20 or 40 US$ carbon price is assumed. Overall these results are in stark contrast to those presented in Table 3. The impact of technology learning is profound and makes wind power a very attractive option even in the absence of other policy instruments (although, as noted above, the results are sensitive to the specific learning rate estimate used). It should be noted of course that the estimated cost reductions for wind power will be realized only in the case where wind power capacity increases substantially. Still, from a Swedish domestic policy perspective the presence of strong international learning spillovers may provide incentives to free-ride on R&D and policy efforts pursued in other countries (see also [31]). Our results confirm that the economic incentive to pursue such a 'wait-and-see' strategy may be significant, and this thus strengthens the argument for international commitments in the renewable power field to ensure efficient diffusion patterns across countries.

Table 6 and Fig. 3 present the same type of cost simulation but now assuming that natural gas prices increase by 38% (as indicated in the European Commission scenario). Increasing gas price of course causes CCGT to become more expensive over time, hence

Table 6
The economics of CCGT and wind power generation in the presence of climate policy, technology learning and increasing gas prices.

	20 US$ $r = 5\%$	40 US$	20 US$ $r = 10\%$	40 US$
	Learning rates: wind 0.23; gas 0.10			
Wind 40	Wind cheaper	Wind cheaper	Wind cheaper	Wind cheaper
Wind 150	Wind cheaper	Wind cheaper	Gas cheaper	Wind cheaper
	Learning rates: wind 0.11; gas 0.10			
Wind 40	Wind cheaper	Wind cheaper	Gas cheaper	Wind cheaper
Wind 150	Gas cheaper	Wind cheaper	Gas cheaper	Gas cheaper

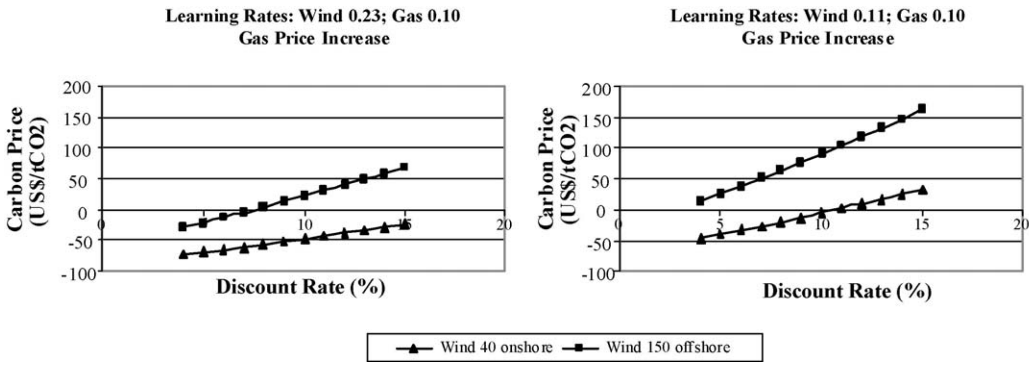

Fig. 3. Carbon prices required to equalize the cost of wind power with the cost of CCGT (technology learning and gas price increase included) (US$/t$CO_2$).

increasing its life time generation cost. Still, overall the impact of this gas price increase does not appear as profound as the impact of technology learning in the wind power sector.

The above exercise shows that the estimated cost reduction for wind power is heavily dependent on the exogenously given capacity increase that is assumed to take place and the associated learning rate. This is also true for CCGT but here the learning rate is lower since it is a more mature technology, and therefore the cost reduction could be relatively modest. Still, these factors are difficult to forecast. Some studies show that there is a risk that the introduction of renewable energy will be delayed. McWeigh et al. [32] suggest that the renewable energy technologies have often failed to penetrate market segments and that the expected penetration levels have typically been much higher than the realized levels. The reason is not necessarily that renewable electricity have failed in itself; the cost reductions for renewable energy sources have often exceeded the initial expectations but cost reductions for the traditional power technologies have been just as (or even more) impressive and institutional obstacles (e.g., time-demanding permitting processes) have also added to the limited diffusion of renewable energy technologies.

4. Concluding remarks

This paper has presented an analysis of how future investment in different power technologies in Sweden could develop under a carbon pricing policy. The results suggest that renewable power will benefit from existing climate policy measures since these imply that cheap technologies such as CCGT will become relatively more expensive, but overall additional policy instruments are also needed to stimulate the diffusion of renewable power. For instance, base-line projections from the European Commission [26] suggest that the EU ETS price will not exceed 40 US$ until 2030. With such a price on carbon only onshore wind power could compete with CCGT, and this only in the case of a low discount rate (e.g., 5%). Renewable power (and in particular wind power) looses competitive ground with the use of higher rate-of-return requirements, and an effective way of promoting renewable electricity is therefore to reduce future uncertainties about policies and regulations. Wind power expansion in particular requires *new* investment on new sites, while the current economic environment tends to favor investments in – and intensified use of – *existing* capacity at existing sites (such as nuclear and hydropower lifetime extension). This introduces a large degree of path dependence in the energy system, and harms all new investments in power generation technologies in Sweden (including also CCGT).

The above outcomes will however be strongly dependent on the assumptions made about technology learning. In the paper we argue that technological learning in Swedish wind power is strongly related to the presence of international learning and R&D spillovers, and for this reason capacity expansions abroad have important influences on the future cost of wind power in the country. The results show that under the European Commission scenario, and using estimated learning rates for wind power and CCGT, wind power gains considerable competitive ground due to technology learning impacts, and the simulations even indicate that as of 2030 onshore wind power will be in no need of explicit policy support. These results are, however, very sensitive to the assumed learning-by-doing rates for wind power and CCGT, respectively.

The importance of international learning and R&D spillovers for a small open economy as the Swedish one may induce national governments to free-ride on foreign R&D and development efforts, thus undermining the objective of large-scale deployment of renewable electricity. Our results confirm that such incentives may exist, thus motivating the introduction of international agreements to stimulate such a development.

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Appendix. Learning rate estimates

In order to estimate the learning rate for Swedish wind power we begin by taking the natural logarithm of Eq. (4) in Section 2 and we obtain an econometric specification of the learning curve equation:

$$\ln I_t = b_0 + b_1 \ln CI_t + b_2 \ln K_t + e_t \tag{A1}$$

where b_0, b_1 and b_2 are parameters to be estimated and e an error term.

The data used to estimate the learning curve for Swedish wind power consist of windmill investment costs in Sweden (in SEK per KWh), cumulative installed capacity of windmills in the world (in MW) and the cumulative wind power R&D expenses in Denmark (in SEK). The Swedish investment cost data have been collected from Ek [37]. Cumulative capacity stems from IEA/OECD Net Electrical Capacity [38]. Annual R&D data have been collected from IEA Energy Technology R&D Budgets and used to construct the R&D expenses [39]. The time lag between R&D expenses and their

Table A1
Descriptive statistics.

Variable	Observation	Mean	Standard deviation	Minimum	Maximum
Investment cost Sweden (I_t)	12	1175.5	195.7	869.6	1446.4
World capacity (CI_t)	12	9352.2	8398.3	2624.0	28378.0
R&D stock Denmark (K_t)	12	122.0	23.1	87.3	157.1

Table A2
Parameter estimates for learning curve equation, dependent variable: investment cost Sweden (I_t).

Variables	Estimates	t Ratios
Constant	18.835	3.640*
World capacity (CI_t)	−0.377	−2.584**
R&D stock Denmark (K_t)	−1.965	−1.965***
Time	0.147	1.875***
R^2	0.86	

* Statistical significance at 1% level.
** Statistical significance at 5% level.
*** Statistical significance at 10% level.

addition to the knowledge stock and the depreciation rate of the knowledge stock follows findings in previous studies (e.g., [13]). Thus, the time lag is set to 2 years and the depreciation rate to 3%. Descriptive statistics for the variables used in the econometric analysis are displayed in Table A1.

The results for our learning curve equation are displayed in Table A2. We tested for the null hypothesis of no serial correlation by performing a LM test against its alternative of serial correlation [40]. The test statistics indicated that we could reject the null hypothesis of zero autocorrelation and for that reason the estimates were corrected for auto-correlation applying the Prais–Winsten procedure. In order to test for general technological progress not captured by any of the other variables (or other time-varying factors) we include a linear time trend in the regression.

The overall fit of the model is good with a R^2 value of 0.86. The parameter estimates for world capacity, the knowledge stock in Denmark and the linear time trend are all statistically significant and in the case of the learning-by-doing and learning-by-searching impacts, the signs are as expected. In our case the time trend coefficient turns out to be positive. The parameter estimates imply that the learning-by-doing rate is 0.23 and the spillover effect from learning-by-searching in Denmark is estimated at a rate of 0.74. This implies that a doubling of installed international capacity and R&D knowledge stock in Denmark would propel capitals cost to decrease by 23% and 74%, respectively. While our estimate of the learning-by-doing rate is in line with previous research the corresponding rate for learning-by-searching must be considered high. In the analysis in Section 3 of this paper, we only make use of the learning-by-doing rate, with the caveat that most other studies have focused on domestic R&D impacts. Simulations based on the Danish R&D impacts would also require future projections of how this knowledge stock will develop our time (and given that Sweden still would import a majority of the wind turbines from Denmark).

Overall the results – although preliminary given the short time series – show that both international technology learning as well as Danish R&D spillovers have historically played roles in influencing the investments costs for wind power in Sweden. We also attempted to include a Swedish R&D-based knowledge stock in the estimation, but this turned out to be statistically insignificant.

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